



Inflated Uncertainty in MultimodelBased Regional Climate Projections

Madsen, Marianne Sloth; Langen, Peter L.; Boberg, Fredrik; Christensen, Jens Hesselbjerg

Published in:
Geophysical Research Letters

DOI:
[10.1002/2017GL075627](https://doi.org/10.1002/2017GL075627)

Publication date:
2017

Document version
Publisher's PDF, also known as Version of record

Document license:
[CC BY](#)

Citation for published version (APA):
Madsen, M. S., Langen, P. L., Boberg, F., & Christensen, J. H. (2017). Inflated Uncertainty in MultimodelBased Regional Climate Projections. *Geophysical Research Letters*, 44(22), 606-613.
<https://doi.org/10.1002/2017GL075627>

RESEARCH LETTER

10.1002/2017GL075627

Key Points:

- The spread in projected climate change is inflated at the global scale when multimodel ensembles are analyzed using grid point statistics
- If the largest regional changes projected by the model ensemble are selected in each region, this is not consistent at the global scale
- Impact analyses based on grid point statistics may indicate a risk of unwanted future impacts that are not physically realizable

Supporting Information:

- Supporting Information S1

Correspondence to:

M. S. Madsen,
msm@dmu.dk

Citation:

Madsen, M. S., Langen, P. L., Boberg, F., & Christensen, J. H. (2017). Inflated uncertainty in multimodel-based regional climate projections. *Geophysical Research Letters*, 44, 11,606–11,613. <https://doi.org/10.1002/2017GL075627>

Received 10 SEP 2017

Accepted 31 OCT 2017

Accepted article online 6 NOV 2017

Published online 23 NOV 2017

©2017. The Authors.

This is an open access article under the terms of the Creative Commons Attribution-NonCommercial-NoDerivs License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

Inflated Uncertainty in Multimodel-Based Regional Climate Projections

Marianne Sloth Madsen¹ , Peter L. Langen¹ , Fredrik Boberg¹ , and Jens Hesselbjerg Christensen^{1,2,3} 
¹Danish Meteorological Institute, Copenhagen Ø, Denmark, ²Niels Bohr Institute, University of Copenhagen, Copenhagen Ø, Denmark, ³Uni Research Climate, Bergen, Norway

Abstract Multimodel ensembles are widely analyzed to estimate the range of future regional climate change projections. For an ensemble of climate models, the result is often portrayed by showing maps of the geographical distribution of the multimodel mean results and associated uncertainties represented by model spread at the grid point scale. Here we use a set of CMIP5 models to show that presenting statistics this way results in an overestimation of the projected range leading to physically implausible patterns of change on global but also on regional scales. We point out that similar inconsistencies occur in impact analyses relying on multimodel information extracted using statistics at the regional scale, for example, when a subset of CMIP models is selected to represent regional model spread. Consequently, the risk of unwanted impacts may be overestimated at larger scales as climate change impacts will never be realized as the worst (or best) case everywhere.

1. Introduction

Climate scenarios are widely used to explore likely impacts of climate change. For use in risk-based impact analyses, there is an increasing demand for probabilistic climate change information based on multimodel approaches. However, information from multimodel ensembles may be extracted in several ways with different implications for the uncertainty of the resulting climate change projections. Pattern scaling, that is, simple scaling of multimodel mean changes of temperature and precipitation patterns with global mean temperature change, has long been used to generalize climate change information beyond the information available from single climate models (Santer et al., 1990; Tebaldi & Arblaster, 2014).

The sets of simulations available from the Coupled Model Intercomparison Project Phase 3 and Phase 5 (CMIP3 (Meehl et al., 2007) and CMIP5 (Taylor et al., 2011)) have been shown to extract common patterns of regional change of temperature and precipitation, while model spread has been used to gauge the regional agreement between models and thereby assess the significance of the change (Collins et al., 2013; IPCC, 2013a) as well as to inform about the associated uncertainty (Tebaldi et al., 2011). The apparent robustness of climate change patterns together with the observation that a multimodel average often outperforms any individual model when compared to observations (Gleckler et al., 2008) suggests that the multimodel mean of a particular climate variable is indicative of a best estimate of the future pattern of change (Knutti et al., 2010; Knutti & Sedlacek, 2013).

In the multimodel setting, temperature change patterns conform better with a simple scaling than precipitation patterns (Tebaldi & Arblaster, 2014). This result may be explained by a stronger influence from local or larger-scale dynamical processes on the forced signal of precipitation change compared to temperature, which is largely dominated by radiative forcing and large-scale interactions (Hawkins & Sutton, 2011; Tebaldi et al., 2011). Despite this, it has been documented that in an ensemble context, even precipitation patterns scale with global mean temperature (Christensen et al., 2015; Neelin et al., 2006).

It is well established that multimodel ensembles exhibit a wide spread in the patterns of change for a particular scenario (Christensen et al., 2013; IPCC, 2013a). This spread is often portrayed by collecting all available model information and evaluating appropriate statistics for a given climate variable (e.g., mean annual temperature) grid point by grid point using for example certain percentiles (e.g., 25th and 75th) to express likely lower or upper bounds around a median or mean value, that is, ignoring any physical interdependence between grid points. This approach was adopted in the Fifth Assessment Report (IPCC, 2013a) from the Intergovernmental Panel on Climate Change (IPCC), where regional information on projected changes was

provided in an Atlas (IPCC, 2013b), globally as well as for a number of larger regions around the world. It is specifically mentioned in the Atlas that the maps provided do not represent a robust estimate of the uncertainty associated with the projections but rather that “the range of model spread is provided as a simple, albeit imperfect, guide to the range of possible futures (including the effect of natural variability).” Here we identify some additional and potentially highly problematic inconsistencies within this approach and point out that similar inconsistencies may occur in regional applications where subsampling of CMIP models is performed; such approaches are frequently adopted within impacts and adaptation research (e.g., Lutz et al., 2016; McSweeney et al., 2012; Ruane & McDermid, 2017; Wilcke & Bärring, 2016).

2. Data and Methods

The analysis is based on the set of 39 models used in the IPCC Atlas for the RCP8.5 scenario (Table AI.1 in IPCC, 2013b), although for one model we use a different ensemble member (see supporting information Table S1). The temperature and precipitation fields are remapped to a common T42 Gaussian grid with an approximate horizontal resolution of 2.8°. Bilinear interpolation is applied for temperature, whereas precipitation is remapped conservatively (Jones, 1999). Twenty year average changes of annual mean surface air temperature and relative changes of annual mean precipitation are calculated for 2081–2100 relative to 1986–2005. In the analysis, these are ranked both model wise (one pattern for each of the 39 models) and grid point wise, that is, by ranking values of change at each grid point individually and aggregating these into 39 patterns all with contributions from multiple models. Global and regional means of simulated change in temperature and precipitation are then calculated and cumulative distributions are used to compare the number of models/patterns (vertical axis) that reach a certain level of change (horizontal axis) using each of the two ways of ranking.

3. Results and Discussion

Figure 1 shows the spread in projected annual mean temperature change (2081–2100 relative to 1986–2005) using output from the 39 CMIP5 models included in the IPCC Atlas for the RCP8.5 scenario. In Figure 1a, an approach identical to that adopted in the IPCC Atlas is used; that is, information from all 39 models is ranked grid point by grid point. The resulting spread between absolute minimum values and maximum values of change is evident, particularly for all land regions and the two polar regions. In Figure 1b, the models are ranked according to their projected change in global mean temperature (a measure of model climate sensitivity), such that each panel shows temperature changes for one single model. Comparing column by column, differences are particularly evident for the minimum and maximum rankings and also clearly visible at the 25th and 75th percentiles. Similar statistics for projected changes in annual mean precipitation (2081–2100 relative to 1986–2005) are shown in Figure 2. For grid point statistics, the total spread is large in all grid points, giving a range consistent with no change and an apparent large uncertainty almost everywhere. On the other hand, each individual model shows a distinct pattern of change far from the extremes indicated in Figure 2a. The detailed dynamical shifts in atmospheric circulation responsible for the precipitation changes in individual models differ, and displacement of major convergence and divergence zones with just a few hundred kilometers results in large numerical differences. Strongly varying model deficiencies in reproducing observed atmospheric circulation and dominant modes of variability holds part of the signal in the projected precipitation patterns in essence creating the lack of grid point consistency across models highlighted in Figure 2a.

The discrepancy between the two approaches (model versus grid point statistics) at larger scales is illustrated in Figure 3a that compares multimodel cumulative temperature and precipitation statistics. At the global scale, the temperature response is between 2.5 and 5.0 K using model statistics and between 1.9 and 5.8 K using grid point statistics. This illustrates how the overall spread is exacerbated at the global scale (here by 1.4 K) when information is extracted at the grid point level. For precipitation, neither the driest (+2%; i.e., still an overall wetting) nor the wettest (+23%) global mean model response resembles the driest (–23%; a global reduction in precipitation) or wettest (+79%) response obtained from aggregating grid point statistics. Therefore, if the largest changes in precipitation were selected everywhere (whether the driest or wettest response), this would be inconsistent with our physical understanding of the climate system at the global scale (although the exact range of the possible global precipitation response is not easy to quantify as it is

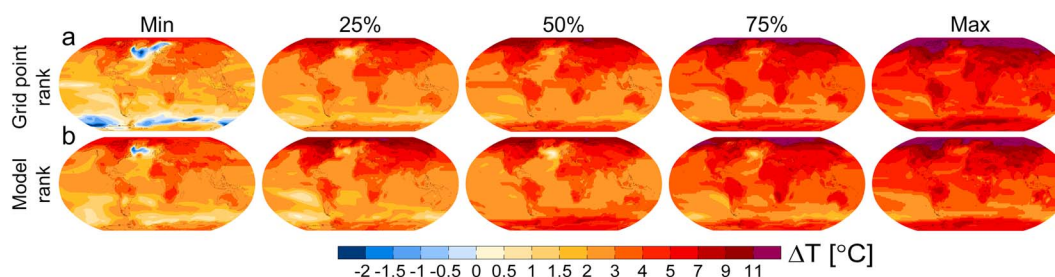


Figure 1. Grid point and model statistics for temperature. Spread in temperature changes (2081–2100 with respect to 1986–2005) for the RCP8.5 scenario using an ensemble of 39 CMIP5 models using two different approaches. (a) The values are ranked grid point by grid point and (b) the models are ranked according to their global mean temperature change.

constrained by the energy budget as well as the atmospheric moisture content (Allen & Ingram, 2002)) and it would be far from that projected by any single model. This further illustrates the dissimilarity in the two approaches. Globally as well as hemispherically, the use of grid point statistics inflates the uncertainty in precipitation so much that the full uncertainty range (minimum to maximum change) based on the individual models is close to the 25%–75% percentile range based on grid point statistics. As Figure 2 suggests, this effect is also present at the continental (Figure 3b) and even at subcontinental scales. For precipitation in particular, the latter is confirmed by Figure S1 that summarizes the same statistics at the somewhat smaller regions used and presented in the IPCC Atlas (IPCC, 2013b); the discrepancy is, however, larger when aggregated over larger regions. Figures 1 and 2 further illustrate that the physical consistency between temperature and precipitation that exists within each individual model is basically lost in an analysis based on grid point statistics. This issue needs to be addressed as well if physically consistent climate projections of multiple variables are to be extracted from multimodel ensembles (Piani & Haerter, 2012).

Statistics at the grid point level is most often used for illustrative purposes (e.g., in the IPCC Atlas). However, an approach commonly used in impact research uses a similar way of regional ranking to select a subset of climate models to represent the spread in regional climate change projected by the full ensemble (Lutz et al., 2016; McSweeney et al., 2012; Ruane & McDermid, 2017; Wilcke & Bärring, 2016). Figures 4 and 5 compare regional ranking with ranking at the global/grid point scale for Europe, Northern/Central Europe, and the Mediterranean region. The differences between the three approaches are larger for precipitation than for temperature. For Europe as a whole (Figure 4), the regional ranking (d) is a balance between less precipitation in the southern part of the domain and more precipitation to the north; that is, the model with the lowest regional ranking has a large decrease in precipitation in Southern and Central Europe combined with only a small increase in Northern Europe. When the min/max changes are selected in each grid point without further constraints (Figure 4e), there are much larger differences between the two extremes than in the regional approach. For global ranking (Figure 4f), there is no systematic increase in regional precipitation change when going from one extreme to the other (4f, left to right). Figure 5 illustrates that there is a larger similarity in regional and grid point statistics for the smaller regions. This indicates that ranking at the regional scale may lead to similar inconsistencies as ranking at the grid point scale; for each region, the models with the

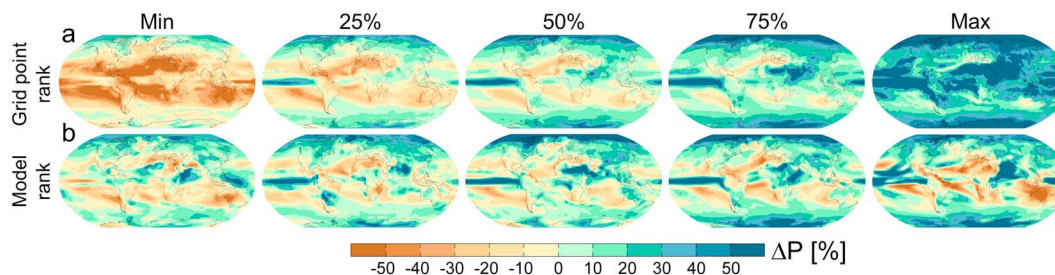


Figure 2. Grid point and model statistics for precipitation. Spread in relative precipitation changes (2081–2100 relative to 1986–2005) for the RCP8.5 scenario using an ensemble of 39 CMIP5 models using two different approaches. (a) The values are ranked grid point by grid point; (b) the models are ranked according to their global mean relative precipitation change.

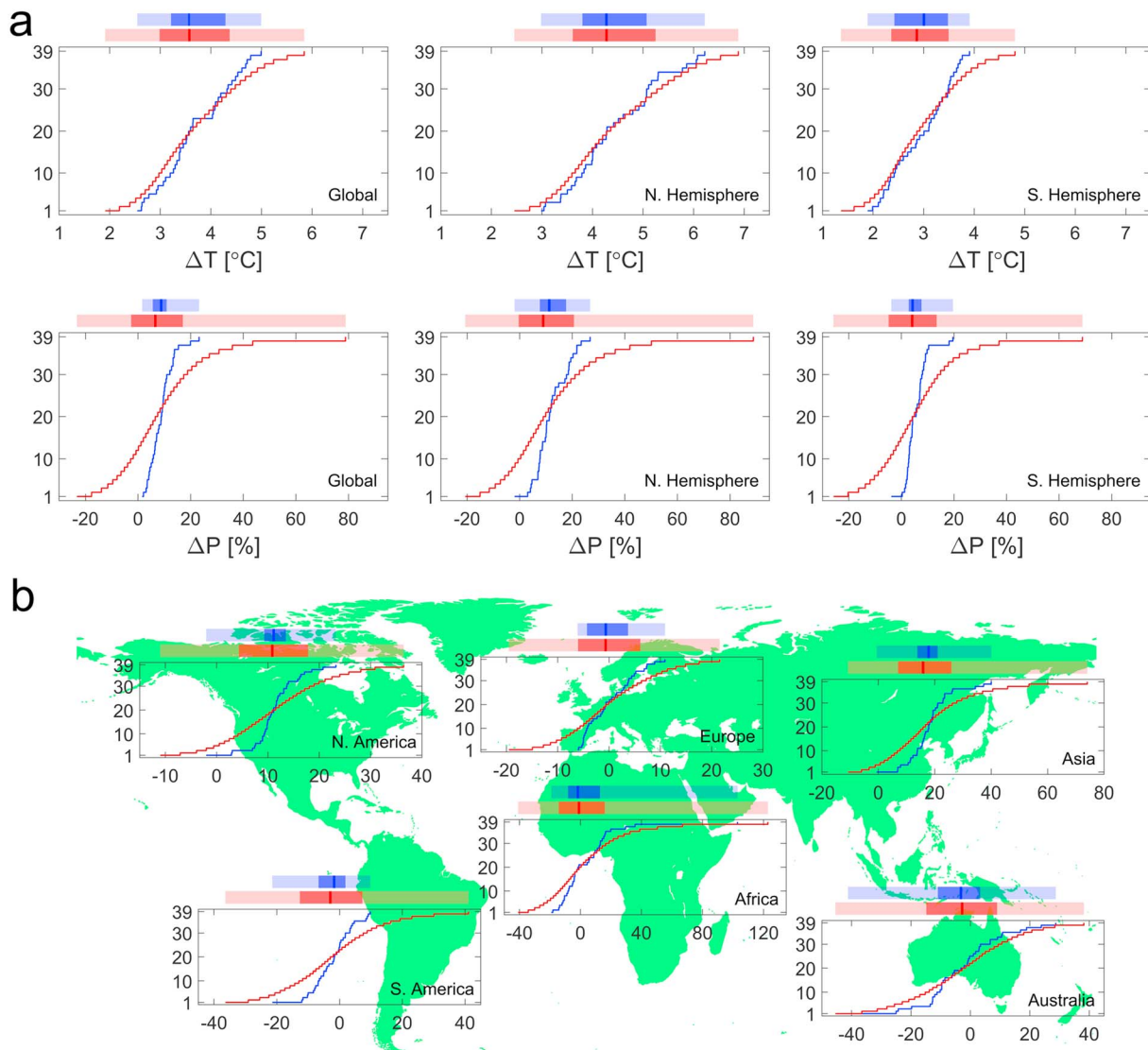


Figure 3. Cumulative statistics. The cumulative distribution of multimodel means of projected changes, that is, the number of models/patterns that has a mean value of change for the region in concern below or equal to the value of change. Blue curves according to regional mean ranking; red curves according to grid point ranking. The horizontal bars denote minimum to maximum ranges (light transparent color), 25th to 75th percentiles (darker transparent color) and median (50%) value (colored vertical line). (a) Global and hemispheric statistics for temperature and precipitation (land plus ocean); (b) continental scale statistics for precipitation (land only).

most extreme local climate change could be selected and aggregated regionally or globally this would result in a larger uncertainty range than projected by the individual models. Similar issues relate to probabilistic regional climate projections (Frieler et al., 2011; Hawkins & Sutton, 2009, 2011; Schleussner, Rogelj, et al., 2016; Schleussner, Lissner, et al., 2016); if the multimodel based climate change signal is chosen in each grid point (or subregion), the associated global mean change would exceed the range projected by the collection of individual models. This also implies that estimating the probability for a change locally in any particular region using the multimodel ensemble statistics prevents a consistent probabilistic statement about the change in any other region, as this would potentially be in conflict with the global mean giving an overall constraint in any given model realization.

Figures 4 and 5 also clearly show that the resulting range of regional changes is smaller, when global ranking is applied, especially for precipitation where there is no systematic increase. Regional climate processes may generate a range of regional climate change signals which are important locally but without having a large impact on the global ranking. In this case, we do not capture the regional range of climate change signals

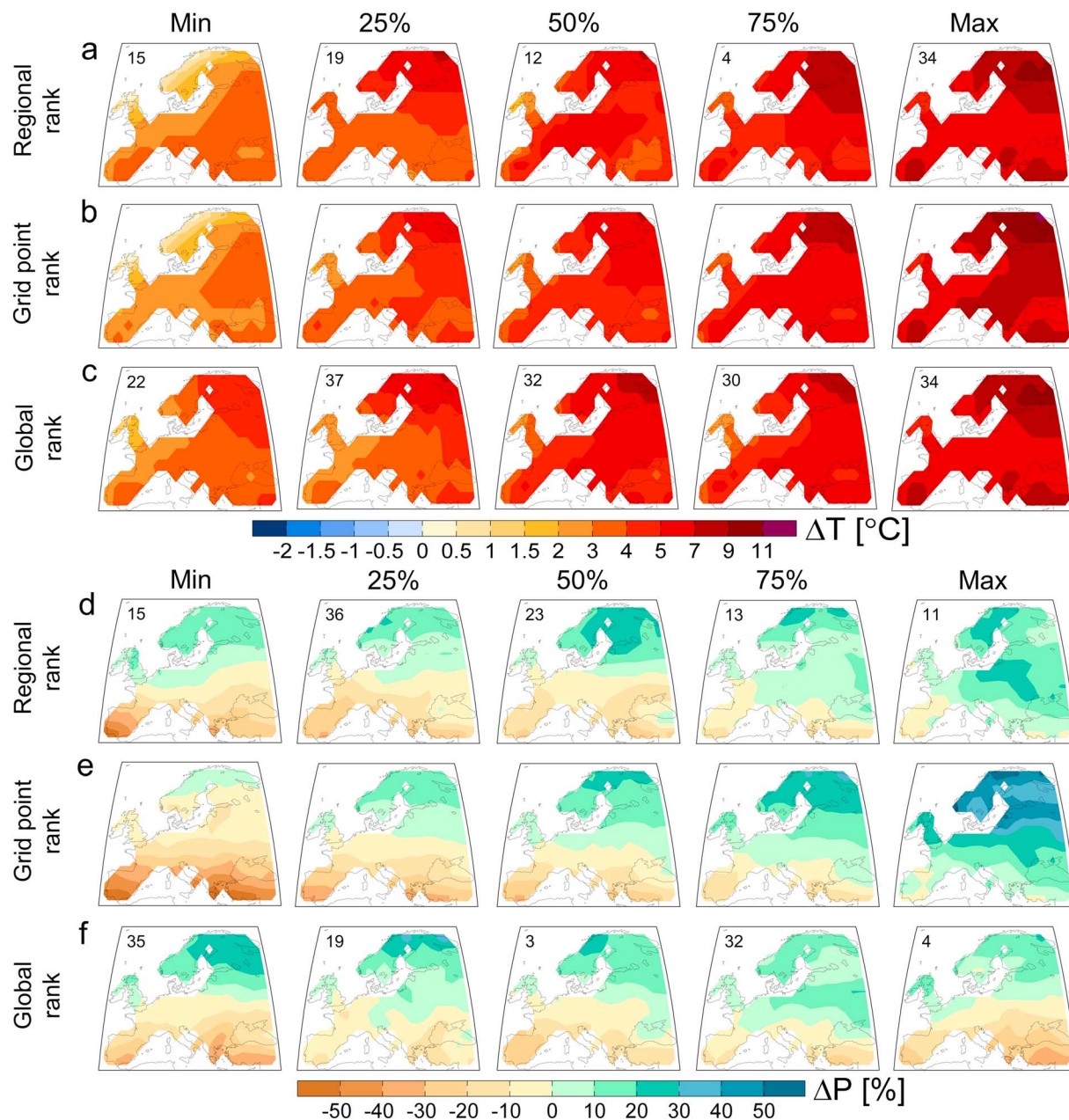


Figure 4. Grid point and model statistics for Europe. Spread in temperature and relative precipitation changes (2081–2100 with respect to 1986–2005) for the RCP8.5 scenario and an ensemble of 39 CMIP5 models using three different approaches. (a and d) The models are ranked according to their regional mean change in precipitation, (b and e) the values are ranked grid point by grid point, and (c and f) the models are ranked according to their global mean precipitation change. The inserted number identifies the model shown (see supporting information Table S1).

which is constrained by the global ranking. This implies that impact studies relying on global selection criteria, for example, (Warszawski et al., 2014) are consistent at the global scale (McSweeney & Jones, 2016) but at the expense of underestimating the regional model spread as projected by the full ensemble. These issues also need to be addressed when global climate models are selected for dynamical downscaling over multiple regions (McSweeney et al., 2015). Applying a multimodel dynamical downscaling approach as adopted by CORDEX (Giorgi & Gutowski, 2015) and in previous coordinated experiments, for example, PRUDENCE (Christensen et al., 2007) and ENSEMBLES (Christensen et al., 2010) using grid point-based statistics further exacerbates the apparent model spread (Deque et al., 2007; Jacob et al., 2014). While climate change impacts are realized locally, the aggregated impacts on larger scales will never be realized

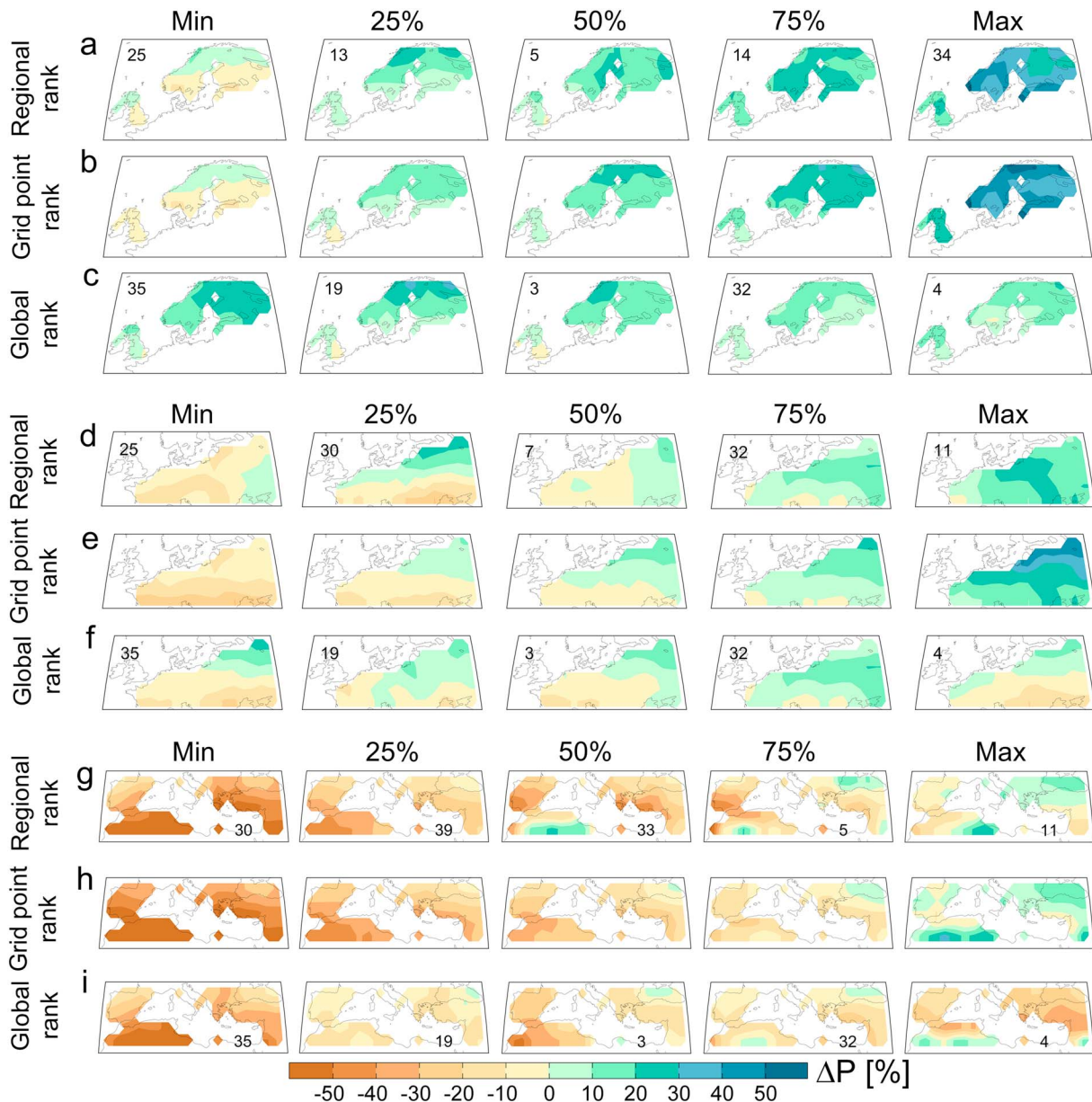


Figure 5. Grid point and model statistics for Northern Europe, Central Europe, and the Mediterranean region. Spread in relative precipitation changes (2081–2100 with respect to 1986–2005) for the RCP8.5 scenario and an ensemble of 39 CMIP5 models using three different approaches. (a, d, and g) The models are ranked according to their regional mean change in precipitation, (b, e, and h) the values are ranked grid point by grid point, and (c, f, and i) the models are ranked according to their global mean precipitation change.

as the worst or best case everywhere. The causal interlinkages between regional change as realized through recognizable patterns of change (e.g., as found by individual models) are important teleconnections that limit the validity of any implicit assumption about local independence of change; that is, the laws of physics constrain the statistics.

4. Conclusions

We have shown that grid point statistics grossly degrades available patterns of information present in multi-model climate projections and consequently inflates uncertainty estimates based on a multimodel ensemble. We further point out that similar inconsistencies arise when subsets of climate models are selected based on regional criteria or when regional probabilistic projections are applied using global models. If global selection

criteria are used instead, the plausible range of projections may be underestimated at the regional scale. Using statistics based on values ranked at the grid point or very local level therefore poses a major problem at the global, continental, and regional scales as it severely inflates the uncertainty as represented by model spread. An important consequence of this finding is that impact analyses relying on multimodel information based on grid point ranked statistics will indicate a likelihood of highly unwanted future impacts, a risk primarily resulting from the inflated uncertainty and unlikely to be physically realizable. Such analyses may lead to costly overadaptation and hence maladaptation. These caveats should be carefully considered when multimodel projections are used in impact studies, and any selection of subensembles should be based on appropriate, well-argued, and transparent choices.

Acknowledgments

We acknowledge the World Climate Research Programme's Working Group on Coupled Modeling, which is responsible for CMIP, and we thank the climate modeling groups (Table S1) for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals. The research leading to these results is part of the EU FP7 project IMPRESSIONS (<http://impressions-project.eu/>) under grant agreement 603416 and also received funding from the ECMWF/Copernicus project DECM/C3S_51_LOT4 and the European Research Council under the EU FP7/ERC grant agreement 610055 as part of the ice2ice project.

References

- Allen, M., & Ingram, W. (2002). Constraints on future changes in climate and the hydrologic cycle. *Nature*, 419(6903), 224–232. <https://doi.org/10.1038/nature01092>
- Christensen, J. H., Carter, T. R., Rummukainen, M., & Amanatidis, G. (2007). Evaluating the performance and utility of regional climate models: The PRUDENCE project. *Climatic Change*, 81(S1), 1–6. <https://doi.org/10.1007/s10584-006-9211-6>
- Christensen, J. H., Krishna Kumar, K., Aldrian, E., An, S.-I., Cavalcanti, I. F. A., de Castro, M., ... Zhou, T. (2013). Climate Phenomena and their Relevance for Future Regional Climate Change. In T. F. Stocker, et al. (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1217–1308). Cambridge, UK and New York: Cambridge University Press. <https://doi.org/10.1017/CBO9781107415324.028>
- Christensen, J. H., Kjellstrom, E., Giorgi, F., Lenderink, G., & Rummukainen, M. (2010). Weight assignment in regional climate models. *Climate Research*, 44(2–3), 179–194. <https://doi.org/10.3354/cr00916>
- Christensen, O. B., Yang, S., Boberg, F., Maule, C. F., Thejll, P., Olesen, M., ... Christensen, J. H. (2015). Scalability of regional climate change in Europe for high-end scenarios. *Climate Research*, 64(1), 25–38. <https://doi.org/10.3354/cr01286>
- Collins, M., Knutti, R., Arblaster, J., Dufresne, J.-L., Fichet, T., Friedlingstein, P., ... Wehner, M. (2013). Long-term Climate Change: Projections, Commitments and Irreversibility. In T. F. Stocker, et al. (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1029–1136). Cambridge, UK and New York: Cambridge University Press. <https://doi.org/10.1017/CBO9781107415324.024>
- Deque, M., Rowell, D. P., Luthi, D., Giorgi, F., Christensen, J. H., Rockel, B., ... van den Hurk, B. (2007). An intercomparison of regional climate simulations for Europe: Assessing uncertainties in model projections. *Climatic Change*, 81(S1), 53–70. <https://doi.org/10.1007/s10584-006-9228-x>
- Frieler, K., Meinshausen, M., Mengel, M., Braun, N., & Hare, W. (2011). A scaling approach to probabilistic assessment of regional climate change. *Journal of Climate*, 25(9), 3117–3144.
- Giorgi, F., & Gutowski, W. J. (2015). Regional dynamical downscaling and the CORDEX initiative. *Annual Review of Environment and Resources*, 40(1), 467–490. <https://doi.org/10.1146/annurev-environ-102014-021217>
- Gleckler, P. J., Taylor, K. E., & Doutriaux, C. (2008). Performance metrics for climate models. *Journal of Geophysical Research*, 113, D06104. <https://doi.org/10.1029/2007JD008972>
- Hawkins, E., & Sutton, R. (2009). The potential to narrow uncertainty in regional climate predictions. *Bulletin of the American Meteorological Society*, 90(8), 1095–1107. <https://doi.org/10.1175/2009BAMS2607.1>
- Hawkins, E., & Sutton, R. (2011). The potential to narrow uncertainty in projections of regional precipitation change. *Climate Dynamics*, 37(1–2), 407–418. <https://doi.org/10.1007/s00382-010-0810-6>
- IPCC (2013a). In T. F. Stocker, et al. (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (1535 pp.). Cambridge, UK and New York: Cambridge University Press. <https://doi.org/10.1017/CBO9781107415324>
- IPCC (2013b). Annex I: Atlas of Global and Regional Climate Projections [van Oldenborgh, G. J., M. Collins, J. Arblaster, J. H. Christensen, J. Marotzke, S. B. Power, M. Rummukainen and T. Zhou (eds.)]. In T. F. Stocker, et al. (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1311–1394). Cambridge, UK and New York: Cambridge University Press. <https://doi.org/10.1017/CBO9781107415324.029>
- Jacob, D., Petersen, J., Eggert, B., Alias, A., Christensen, O. B., Bouwer, L. M., ... Yiou, P. (2014). EURO-CORDEX: New high-resolution climate change projections for European impact research. *Regional Environmental Change*, 14(2), 563–578. <https://doi.org/10.1007/s10113-013-0499-2>
- Jones, P. W. (1999). First- and second-order conservative remapping schemes for grids in spherical coordinates. *Monthly Weather Review*, 127(9), 2204–2210. [https://doi.org/10.1175/1520-0493\(1999\)127%3C2204:FASOCR%3E2.0.CO;2](https://doi.org/10.1175/1520-0493(1999)127%3C2204:FASOCR%3E2.0.CO;2)
- Knutti, R., Abramowitz, G., Collins, M., Eyring, V., Gleckler, P. J., Hewitson, B., & Mearns, L. (2010). Good practice guidance paper on assessing and combining multi model climate projections (Rep.). Bern, Switzerland: IPCC Working Group I Technical Support Unit, University of Bern.
- Knutti, R., & Sedlacek, J. (2013). Robustness and uncertainties in the new CMIP5 climate model projections. *Nature Climate Change*, 3(4), 369–373.
- Lutz, A. F., ter Maat, H. W., Biemans, H., Shrestha, A. B., Wester, P., & Immerzeel, W. W. (2016). Selecting representative climate models for climate change impact studies: An advanced envelope-based selection approach. *International Journal of Climatology*, 36(12), 3988–4005. <https://doi.org/10.1002/joc.4608>
- McSweeney, C. F., & Jones, R. G. (2016). How representative is the spread of climate projections from the 5 CMIP5 GCMs used in ISI-MIP? *Climate Services*, 1, 24–29. <https://doi.org/10.1016/j.cliser.2016.02.001>
- McSweeney, C. F., Jones, R. G., & Booth, B. B. B. (2012). Selecting ensemble members to provide regional climate change information. *Journal of Climate*, 25(20), 7100–7121. <https://doi.org/10.1175/JCLI-D-11-00526.1>
- McSweeney, C. F., Jones, R. G., Lee, R. W., & Rowell, D. P. (2015). Selecting CMIP5 GCMs for downscaling over multiple regions. *Climate Dynamics*, 44(11–12), 3237–3260. <https://doi.org/10.1007/s00382-014-2418-8>
- Meehl, G., Covey, C., Delworth, T., Latif, M., McAvaney, B., Mitchell, J., ... Taylor, K. (2007). The WCRP CMIP3 multimodel dataset—A new era in climate change research. *Bulletin of the American Meteorological Society*, 88(9), 1383.

- Neelin, J. D., Munnich, M., Su, H., Meyerson, J. E., & Holloway, C. E. (2006). Tropical drying trends in global warming models and observations. *Proceedings of the National Academy of Sciences*, 103(16), 6110–6115. <https://doi.org/10.1073/pnas.0601798103>
- Piani, C., & Haerter, J. O. (2012). Two dimensional bias correction of temperature and precipitation copulas in climate models. *Geophysical Research Letters*, 39, L20401. <https://doi.org/10.1029/2012GL053839>
- Ruane, A. C., & McDermid, S. P. (2017). Selection of a representative subset of global climate models that captures the profile of regional changes for integrated climate impacts assessment. *Earth Perspectives*, 4(1), 1.
- Santer, B. D., Wigley, T. M. L., Schlesinger, M. E., & Mitchell, J. F. B. (1990). Developing climate scenarios from equilibrium GCM results (Rep.). (29 pp.). Hamburg, Germany: Max-Planck-Institut-für-Meteorologie.
- Schleussner, C., Lissner, T. K., Fischer, E. M., Wohland, J., Perrette, M., Golly, A., ... Schaeffer, M. (2016). Differential climate impacts for policy-relevant limits to global warming: The case of 1.5 degrees C and 2 degrees C. *Earth System Dynamics*, 7(2), 327–351. <https://doi.org/10.5194/esd-7-327-2016>
- Schleussner, C., Rogelj, J., Schaeffer, M., Lissner, T., Licker, R., Fischer, E., ... Hare, W. (2016). Science and policy characteristics of the Paris agreement temperature goal. *Nature Climate Change*, 6(9), 827–835. <https://doi.org/10.1038/nclimate3096>
- Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2011). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, 93(4), 485–498.
- Tebaldi, C., & Arblaster, J. (2014). Pattern scaling: Its strengths and limitations, and an update on the latest model simulations. *Climatic Change*, 122(3), 459–471. <https://doi.org/10.1007/s10584-013-1032-9>
- Tebaldi, C., Arblaster, J., & Knutti, R. (2011). Mapping model agreement on future climate projections. *Geophysical Research Letters*, 38, L23701. <https://doi.org/10.1029/2011GL049863>
- Warszawski, L., Frieler, K., Huber, V., Piontek, F., Serdeczny, O., & Schewe, J. (2014). The inter-sectoral impact model intercomparison project (ISI-MIP): Project framework. *Proceedings of the National Academy of Sciences*, 111(9), 3228–3232. <https://doi.org/10.1073/pnas.1312330110>
- Wilcke, R. A. I., & Bärring, L. (2016). Selecting regional climate scenarios for impact modelling studies. *Environmental Modelling & Software*, 78, 191–201. <https://doi.org/10.1016/j.envsoft.2016.01.002>